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Comparison of MobileNetv2 and MobileNetv3 architectures in rice leaf disease classification using transfer learning

Adlim Miftahuddin[1], Moch. Lutfi[2], Zulfatun Nikmatus Saadah[3]
[1,2,3]Departement of Informatics Engineering, Faulty of Engineering, Universitas Yudharta Pasuruan, Pasuruan, Indonesia

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ABSTRACT

Rice is of the main food commodities in Indonesia that is susceptible to various leaf diseases, one of which is Bacterial Blight, Brown Spot, and Leaf Smut. Manual identification by farmers is often less accurate and time-consuming, thus requiring a technology-based detection system. The objective of this research is to categorize rice leafdiseases through the use of deep learning with a transfer learning approach based on MobileNetV2 and MobileNetV3 architectures. The dataset, comprising 4,684 rice leaf images, was divided into training and validation sets using an 80:20 ratio. Preprocessing included resizing images to 224×224 pixels, normalization, and augmentation to increase data variation. Training was carried out across 30 epochs with a mini-batch size set to 32. while applying an EarlyStopping mechanism to reduce the likelihood of overfitting. The result of the experiment indicate that MobileNetV2 reached an 96% accuracy, while MobileNetV3 outputperformed is with an accuracy of 99%. Therefore, MobileNetV3 is more effective for rice leaf disease classification.

Corresponding Author:

Moch. Lutfi,
Departement of Informatics Engineering,
Faculty of Engineering,
Universitas Yudharta Pasuruan,
Jl. Yudharta No. 07 (Pesantren Ngalah) Sengonagung Purwosari Pasuruan, Jawa Timur, 67162, Indonesia
Email: moch.lutfi@yudharta.ac.id

1. INTRODUCTION

Rice (Oryza sativa) is considered one of the world's primary food crops, positioned thord in overall ranking among staple types of grains after maize and wheat (Khoiruddin dkk., 2022). Paddy rice, as the main staple food, meets the needs of nearly half of the world's population (Zhao dkk., 2021). However, rice productivity is highly vulnerable to disturbances, particularly leaf diseases. The major rice leaf diseases that frequently occur and cause significant damage include Bacterial Blight, Brown Spot, and Leaf Smut. These diseases can cause significant damage to leaf tissues, reduce the photosynthesis rate, and directly affect plant growth as well as crop yields (Farihah, 2025).

Nitrogen (N) is a major component of several essential nutrients found in plants (Aminifard dkk., 2012). Nitrogen fertilization, along with appropriate plant density, serves as a key factor in maximizing rice production and nutrient utilization efficiency (Tefera dkk., 2024). Nitrogen fertilization is essential for the formation of well-structured leaves, which influence solar radiation absorption, photosynthesis, and dry matter accumulation in plants (Lai dkk., 2025). However, excessive nitrogen can cause problems such as suboptimal plant growth, disruption of the balance between growth and disease resistance, and fluctuations in crop yields (Sun dkk., 2024). To determine the nitrogen requirements of rice plants, the Leaf Color Chart (LEC) is recommended (Efendi, 2012). Although practical, this manual method has limitations due to the subjective nature of observations, resulting in low accuracy and inefficient application, especially in large areas. (Sedo dkk., 2019).

As a solution, artificial intelligence-based approaches offer a more efficient and accurate alternative. Analysis of rice leaf images through classification techniques allows the system to transform images into numerical representations for processing using machine learning algorithms (Ramesh & Vydeki, 2020)(Abdullah dkk., 2025). The development of deep learning has produced promising image-based plant stress detection methods (Yang dkk., 2025). CNNs have been shown to accurately classify images (S dkk., 2024). with various architectures such as AlexNet, VGGNet, ResNet, DenseNet, and MobileNet demonstrating high performance. ResNet-50 was successfully applied to classify Robusta coffee leaf diseases (Suprihanto dkk., 2022). while MobileNet was used to detect cassava leaf diseases with 88% training accuracy and 84% testing accuracy (Arafat dkk., 2025). Thus, AI-based systems can reduce subjectivity, improve accuracy, and accelerate decision-making compared to manual BWD methods.

According to prior research, the Convolutional Neural Network (CNN) algorithm has been extensively utilized for object recognition tasks. Among the commonly adopted architectures in deep learning is LeNet-5 (Yadav dkk., 2024), AlexNet (Kumar dkk., 2025), VGGNet (Prasetyo dkk., 2022), GoogLeNet (Chen dkk., 2023), DenseNet (Ma dkk., 2025), and MobileNet (Arafat dkk., 2025).

Based on the issue of rice leaf diseases that can reduce productivity, early detection is crucial. One effective approach is to utilize image processing technology based on deep learning to automatically identify disease symptoms on leaves. In this study, transfer learning methods with the MobileNetV2 and MobileNetV3 architectures are employed to reduce the risk of overfitting and improve performance compared to previous approaches. The evaluation is conducted using accuracy, precision, recall, and F1-score metrics to comprehensively assess the model’s performance.

2. RESEARCH METHOD

This research introduces a deep transfer learning approach for identifying rice plant diseases through leaf color chart patterns. The approach employs deep learning architectures including MobileNetV2 and MobileNetV3, with performance evaluated using accuracy, precision, recall, and F1-score.

Data Collection

This study uses a dataset of rice leaf images consisting of 4,684 samples classified into three categories of disease, namely Bacterial Blight, Brown Spot, and Leaf Smut. The dataset was obtained from Kaggle.com, with all images stored in .jpg format and having varying resolutions. The images were then organized into folders according to their respective classes and used as the primary material for training and testing the classification model based on MobileNetV2 with a transfer learning approach.

Dataset Splitting

The dataset used in this study is divided into three subsets: training set, validation set, and testing set. This division aims to ensure that the model can be properly trained, parameters can be tuned to prevent overfitting, and the model can be evaluated using unseen data. In this study, the dataset was split with a proportion of 80% for training and 20% for validation and testing. This proportion was chosen based on common standards in deep learning research, where the training data should be larger to allow the model to effectively learn patterns, while the validation data is used to assess the model’s generalization capability (*RAHMADHAN ADINUGROHO-FST*, t.t.).

The dataset partitioning can be formulated as follows:

$$|D_{train}|=0.8\times|D|$$

$$|D_{val}|=0.2\times|D|$$

Explanation:

- D = the entire dataset
- D_{train} = training dataset (80%)
- D_{val} = validation/testing dataset (20%)

Data Preprocessing

Data preprocessing is a stage carried out before image data is used in the model training process. The purpose of preprocessing is to standardize image sizes, normalize pixel values, and enrich data variation through augmentation techniques. With preprocessing, the model is expected to recognize image patterns more optimally, reduce the risk of overfitting, and improve accuracy in the classification stage (Anissa Ollivia Cahya Pratiwi, 2023). The preprocessing steps conducted in this study include Figure 1 :

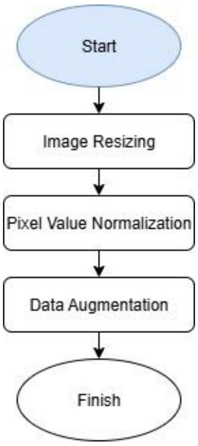

Figure 1. Data preprocessing

System Implementation

Figure 3.3 illustrates the stages of the research procedure, which include data input, preprocessing, data partitioning, model training, and system evaluation.

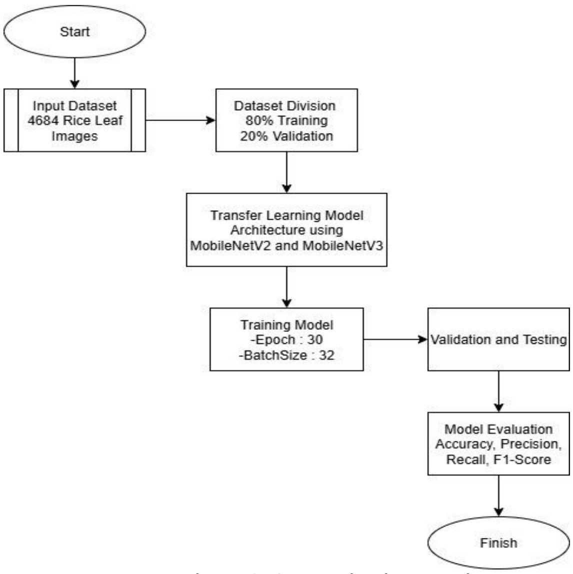

Figure 2. System implementation

MobileNetV2 Model Architecture

The model architecture used in this study is MobileNetV2 with a transfer learning approach. MobileNetV2 was chosen because it is lightweight, computationally efficient, and still capable of providing good classification performance on image data. According to (Annur dkk., 2023), MobileNetV2 employs the depthwise separable convolution technique, which is capable of notably minimizing the number of parameters and computational demands while maintaining the model's accuracy.

In this study, the MobileNetV2 architecture was utilized as the base model for the feature extraction process of rice leaf images. The original classification layer of MobileNetV2 (the final fully connected layer) was removed and replaced with new layers adjusted to the number of classes in the dataset, namely three classes: Bacterial blight, Brown spot, and Leaf smut. In general, the summary of the obtained architectural parameters is as follows:

Table 1. Parameters for MobileNetV2 architecture

Layer (type)	Output shape	Param #
Conv2d_30 (Conv2d)	(None, 116, 32)	832
Nax_pooling2d_30 (maxpooling)	(None, 58, 158, 32)	0
Conv2d_31 (conv2d)	(None, 56, 156, 64)	18496
Max_pooling2d_31 (maxpooling)	(None, 28, 78, 64)	0
Conv2d_32 (conv2d)	(None, 26, 76, 64)	36928
Max_pooling2d_32 (maxpooling)	(None, 13, 38, 64)	0
Flatten_10n(flatten)	(None. 31616)	0
Dense_20 (Dense)	(None, 128)	4046976
Dense_21 (Dense)	(None,10)	1290

Total parameters: 4,104,522
Trainable parameter: 4,104,522
Non-trainable parameters:0

MobileNetV3 Model Architecture

MobileNetV3 represents a CNN-based architecture designed to enhance computational efficiency while preserving accuracy in image classification. As an extension of MobileNetV2, MobileNetV3 is equipped with squeeze-and-excitation blocks and the hard-swish activation function, and it is designed with two main sets of hyperparameters, resulting in a smaller model size and lower latency. This architecture is highly efficient for mobile devices and embedded systems without reducing classification capability (Firdaus dkk., 2024).

In this study, the MobileNetV3 architecture was utilized as the base model for the feature extraction process of rice leaf images. The final fully connected layer of MobileNetV3, which serves as the original classification layer, was removed and substituted with newly designed layers tailored to the dataset, consisting of three classes: Bacterial blight, Brown Spot, and Leaf Smut. In general, this architecture is designed to produce a compact model with low latency, making it efficient for deployment on resource-constrained devices. The summary of the obtained architectural parameters is as follows:

Table 2. Parameters for MobileNetV3 architecture

Layer (type)	Output shape	Param #
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Conv2d_32 (conv2d)	(None, 26, 76, 64)	36928
Max_pooling2d_32 (maxpooling)	(None, 13, 38, 64)	0
Flatten_10n(flatten)	(None. 31616)	0
Dense_20 (Dense)	(None, 128)	4046976
Dense_21 (Dense)	(None,10)	1290

Total parameters: 2,422,339
Trainable parameter: 164,355
Non-trainable parameters:0

Transfer Learnig

Transfer learning refers to a deep learning approach that utilizes pretrained weights from large-scale models, such as ImageNet, and applies them to a different dataset. This approach accelerates the training process, improves model performance, and helps minimize the risk of overfitting. It is widely applied in image classification tasks, including plant disease detection, as it can achieve optimal performance even with limited datasets (Whardana dkk., 2024).

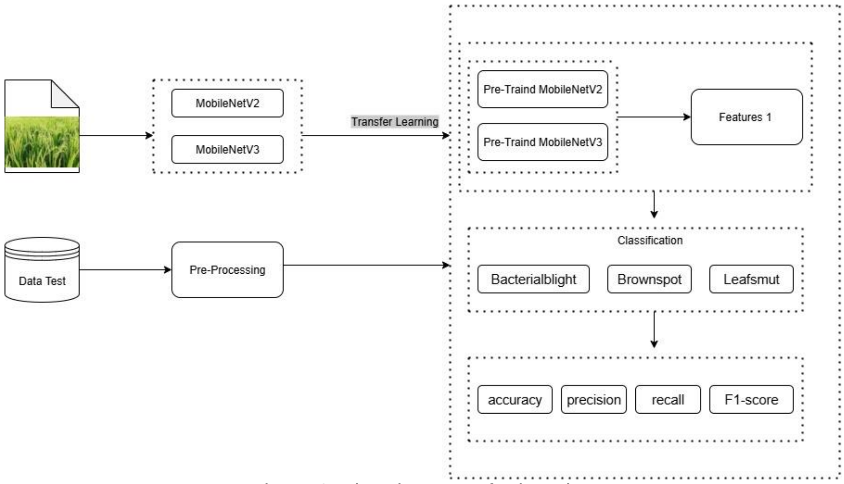

Figure 3. Flowchart transfer learning

3. RESULTS AND DISCUSSIONS

This part presents the implementation of a rice leaf disease classification system utilizing Convolutional Neural Networks (CNN) with the pretrained MobileNetV2 and MobileNetV3 architectures. The models were employed to recognize three major rice diseases, namely blast, blight, and tungro. MobileNetV2 was selected for its efficiency and reliable accuracy in image classification tasks, while MobileNetV3 was used as a comparison due to its more compact design and lower latency, making it suitable for efficient classification without reducing performance. The implementation included training and evaluation processes to measure the models' performance in recognizing disease patterns on rice leaves, The evaluation was carried out using accuracy, precision, recall, and F1-score to measure the generalization ability of the models.

Training and Testing Results of the MobileNetV2 Model

The MobileNetV2 model was trained using rice leaf image datasets that had been preprocessed and augmented. The model training was conducted for up to 30 epochs, with an EarlyStopping mechanism applied to avoid overfitting. The training results showed that the model achieved a training accuracy of 95.58% with a loss value of 0.1187. On the validation data, an accuracy of 95.83% with a loss value of 0.1158 was obtained, which implies that the model generalized effectively.

To visualize the training results, accuracy and loss curves for both training and validation data are presented, as shown in Figure 5 and Figure 6 The accuracy curve demonstrates a stable improvement from the initial to the final epoch, while the loss curve shows a consistent decrease. This indicates that the model successfully learned the patterns without experiencing significant overfitting.

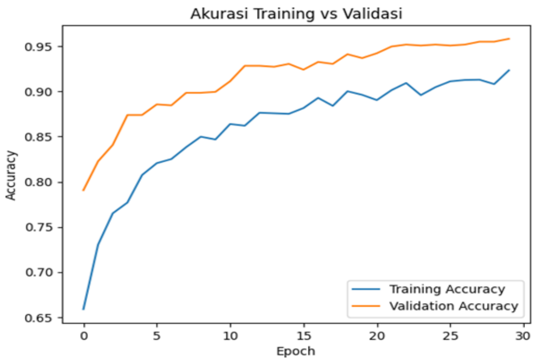

Figure 4. Training and validation accuracy curve

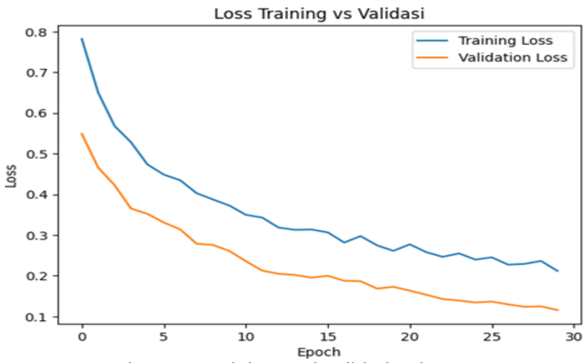

Figure 5 Training and validation loss curve

Evaluation of the MobileNetV2 Model Architecture

Performance was measured using a confusion matrix in combination with metrics such as precision, recall, and F1-score for every class. The experimental results on the test dataset are outlined as follows:

Table 3. Evaluation results of the MobileNetV2 model

Class	Precision	Recall	F1-Score	Support
Bacterial Blight	92.53%	99.38%	95.83%	162
Brown Spot	98.75%	97.53%	98.14%	162
Leaf Smut	97.81%	91.16%	94.37%	147
Accuracy	96.18%	96.18%	96.18%	471

Experimental Results of the MobileNetV3 Model on Training and Testing Data

The training process of the MobileNetV3 model was carried out using rice leaf image datasets that had undergone preprocessing and augmentation. Training was carried out for a maximum of 30 epochs with an EarlyStopping strategy applied to mitigate overfitting. The obtained results indicated that the model reached a training accuracy of 99.36% and a loss of 0.0268. On the validation data, an accuracy of 99.36% with a loss value of 0.0441 was obtained, suggesting that the model exhibited strong generalization ability.

To visualize the training results, accuracy and loss curves for both training and validation data are presented, as shown in Figure 6 and Figure 7 The accuracy curve demonstrates a stable improvement from the initial to the final epoch, while the loss curve shows a consistent decrease. This indicates that the model successfully learned well and did not experience significant overfitting.

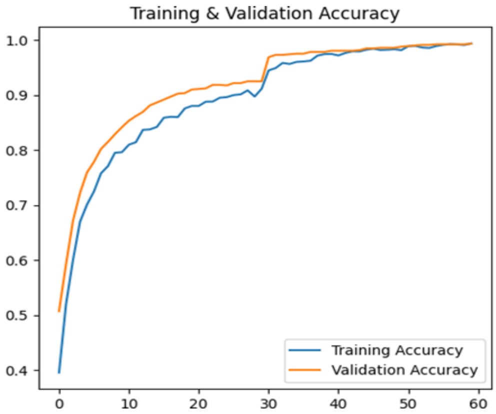

Figure 6. Training and validation accuracy

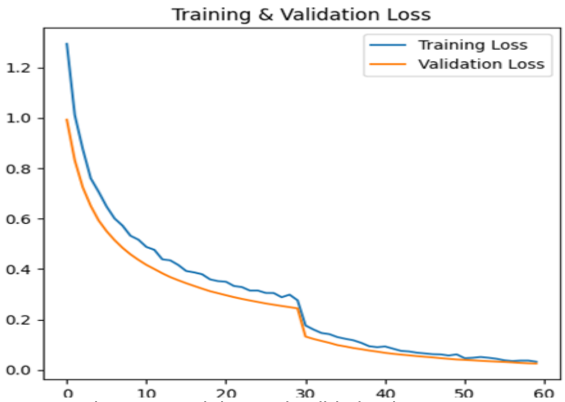

Figure 7. Training and validation loss curve

Evaluation of the MobileNetV3 Model Architecture

The model evaluation was carried out using a confusion matrix along with the calculation of evaluation metrics, namely precision, recall, and F1-score for each class. The following are the results of the model testing on the testing data:

Table 4. Evaluation results of the MobileNetV2 model

Class	Precision	Recall	F1-Score	Support
Bacterial Blight	92.53%	99.38%	95.83%	162
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Leaf Smut	97.81%	91.16%	94.37%	147
Accuracy	96.18%	96.18%	96.18%	471

Model Performance Comparison

The experimental results showed that the MobileNetV2 architecture achieved an accuracy of 96%, while the MobileNetV3 architecture obtained a higher accuracy of 99%. Beyond accuracy, the performance differences between these two models can be explained in terms of model complexity, number of parameters, and inference latency. MobileNetV2, as an earlier architecture, contains a relatively larger number of parameters and requires higher computational resources, which results in longer inference times when deployed on resource-constrained devices. In contrast, MobileNetV3 introduces several architectural optimizations, such as lightweight operations and efficient layer designs, that significantly reduce the number of parameters and computational costs. These improvements not only enhance inference speed but also allow the model to maintain superior accuracy. Consequently, MobileNetV3 is considered more accurate, efficient, and practical for real-time applications, including deployment in smartphone-based systems for smallholder farmers.

4. CONCLUSION

Based on the results of this study on rice leaf disease classification using transfer learning with MobileNetV2 and MobileNetV3 architectures, several conclusions can be drawn. This research employed a dataset of 4,684 rice leaf images, which were classified into three disease categories: Bacterial Blight, Brown Spot, and Leaf Smut. The dataset was divided into 80% for training purposes and 20% for validation. The preprocessing procedures involved resizing the images to 224×224 pixels, normalizing the pixel values with a rescale factor of 1/255, and applying image augmentation techniques to enhance data variability. The model was trained for 30 epochs using a batch size of 32, while an EarlyStopping callback was employed to prevent overfitting and improve generalization.

The testing results showed that the MobileNetV2 architecture achieved an accuracy of 96%, while the MobileNetV3 architecture achieved a higher accuracy of 99%. Therefore, it can be concluded that MobileNetV3 outperforms MobileNetV2 in classifying rice leaf diseases, as it provides better performance on the dataset used. In addition to these findings, it is recommended that the trained MobileNetV3 model be implemented in practical farming contexts, particularly for smallholder farmers. One potential strategy is to integrate the model into a smartphone-based application that allows farmers to capture leaf images and instantly obtain classification results. Such an approach would make the technology more accessible and useful in the field, thereby supporting more efficient and sustainable rice production.

ACKNOWLEDGEMENTS

For future research development, several recommendations can be considered, including increasing the size of the dataset to make the model more robust and capable of better generalizing rice leaf image patterns, experimenting with other CNN architectures such as EfficientNet, InceptionV3, or ResNet to compare model performance, and conducting evaluations using real-time field datasets so that the model's performance can be truly tested under real-world conditions, rather than only on the available datasets.

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